

SIGNAL DETECTION IN ARCTIC UNDER-ICE NOISE

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Abstract

This paper treats a signal detection problem using arctic under-ice noise. The authors have had access to one large segment of data (6150144 samples), which is nonstationary and has been shown to be non-Gaussian. A model is presented for the arctic under-ice noise, and the performance levels achieved by several different detectors are compared. The association between the shape of the empirical probability density function and the shape of the power spectrum is explored. The arctic noise is known to contain narrowband and impulsive components, and it is shown here that removal of the narrowband components results in nearly Gaussian noise.

ARCTIC UNDER-ICE NOISE

In the early 1940's, researchers began examining the characteristics of "open-water" noise [1,2], but it was not until the late 1950's that an interest developed in underwater acoustics in ice-covered areas. The main objectives were to determine average pressure spectra levels (hereafter called noise levels) as a function of weather conditions, and to gain an understanding of the physical processes causing under-ice noise. Under-ice noise levels, for shore-fast and floe ice, were shown to be unaffected by wind speed and to be anisotropic. Several researchers concluded that the majority of under-ice noise was the result of slight movements of the ice itself and temperature gradients causing the ice to crack. They also found that these physical processes resulted in non-Gaussian and impulsive noise, with the noise becoming more Gaussian in nature with increasing depth [3-6].

By the late 1960's, researchers began to concentrate on single records to obtain statistical information about the under-ice environment. This paper involves such an analysis performed on FRAM II data. The data was recorded on 23-24 April 1980, from a pack ice floe, at 86° N. 25° W... An omnidirectional hydrophone, radio linked to a receiver, was suspended to a depth of 91m in 4000m deep water. The data, recorded on an analog device, was bandpass filtered from 0.01-5kHz. Next the data was passed through a lowpass filter with a 2.5kHz cutoff, then it was digitized with a sampling rate of 10kHz. The specific data segment being analyzed was recorded from 11:30 - 11:40 pm on April 23. This segment contains a total of 6,150,144 samples, which is slightly longer than 10 minutes [7,8]. For convenience, it has been broken up into 6006 records of 1024 numbers each.

A number of authors have looked at this data segment. Dwyer [7,9,10] took several different approaches to analyzing the under-ice data. He examined the time-domain data and concluded from an analysis of the first four central moments that the noise is nonstationary and non-Gaussian. The non-Gaussian nature was confirmed when a time-domain energy spectrum was compared to that for a Gaussian noise source. The same techniques

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enabled the identification of narrowband and impulsive components. The existence of these components was not surprising, since the floe was moving slowly throughout the experiment [6,9]. A similar analysis carried out in the frequency domain yielded comparable results.

Veitch and Wilks [8] attempted to develop a model for the under-ice noise. Their work confirms the presence of narrowband and impulsive components, but suggests that the background noise is Gaussian. By examining the first four central moments of the time-domain data in detail, they noted a strong correlation between records with large kurtosis and large skew. They also determined that a large kurtosis was associated with high amplitude bursts. They proposed that the under-ice noise could be modeled as a mixture containing a Gaussian background, high powered sinusoids of random frequency and amplitude, and an impulsive component. We agree that this model is valid, though a specific model for the impulsive component is not presented [see [8] for a detailed discussion of the model].

Since the noise was known to be nonstationary, we began an analysis aimed at estimating the rate at which the statistical characteristics of the noise were changing. Empirical probability density function (epdf) plots were generated, each based on 5 contiguous records (≈ 0.5 sec). Careful examination of the epdf's indicated that the noise could be modeled by a member of the generalized Gaussian family. The generalized Gaussian families of densities can be represented in the form:

$$f(x) = Be^{-(b|x-\mu|)^c}$$

where

$$b = \frac{1}{\sigma} \left[\frac{\Gamma(3/c)}{\Gamma(1/c)} \right]^{\frac{1}{4}} \qquad B = \frac{bc}{2\Gamma(1/c)}$$

where $\mu = \text{mean}$, $\sigma^2 = \text{variance}$, c = the shape parameter, and $\Gamma(\cdot)$ is the gamma function. The other main parameters of interest for this family are the skew and the kurtosis. The skew is zero for all values of c, and the kurtosis can be expressed as:

Kurtosis =
$$\frac{\Gamma(1/c) \Gamma(5/c)}{\Gamma(3/c)^2}$$

It can be easily shown that the kurtosis can take on values as high as 6 when c=1, and as low as 2 when c=6. For $c \in (1,6]$, the relationship between kurtosis and c is one-to-one. A discussion on the usefulness of kurtosis as a measure can be found in [8,11]. A simple time-varying detector structure was implemented where the mean and variance were estimated by the sample mean and sample variance, and the sample kurtosis was used to estimate c. For $c \in (1,6]$, results show that this family models the epdf well if the epdf is nearly symmetric and the kurtosis is less than 4.

For the simple detection problem, we have:

$$H: X_i = N_i$$

$$K: X_i = N_i + s$$

where X_i is the received signal, N_i is the arctic under-ice noise, and s is a positive known signal. Define the false alarm probability, α as:

$$\alpha = P(\text{ decide } K | H \text{ is true})$$

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and the power, β as:

$$\beta = P(\text{ decide } K | K \text{ is true})$$

Define the performance level as the value of β for a given α achieved by a detector, with the goal to find the detector which maximizes the performance level. In order to judge the effectiveness of the generalized Gaussian model for the under-ice noise, the performance levels of the following detectors was compared.

- [D1] The Linear Detector (Neyman-Pearson optimal for Gaussian noise)
- [D2] The Amplitude Limiter Detector (Neyman-Pearson optimal for Laplace noise)
- [D3] The Time-Varying Linear Detector
- [D4] The Time-Varying Generalized Gaussian Detector

To determine the power levels achieved by detector structures (D1) and (D2), it was assumed that the global mean and variance of the noise were known to the detector. From this information, the signal power was determined in order to achieve an overall S/N ratio of unity. The entire data set was then used as an input to the detector in order to calculate the epdf for the detector structure, from which α and β are easily determined. A different approach was used with (D3) and (D4). For these two detectors, the (α,β) pairs were computed for blocks of 5 records (blocks of 5 records were chosen to insure that the data is as stationary as possible within each block), with the mean, variance, and kurtosis of each block known to the detector, which then adjusted the structure and the signal power in order to achieve a S/N ratio of unity. It is emphasized that the structures of (D1) and (D2) are fixed for the entire data set, while the structures of (D3) and (D4) change with every record.

Figure 1 illustrates the (α,β) pairs for (D1) - (D4), where the average levels of β for each α for (D3) and (D4) are plotted. (D2) is optimal in the Neyman-Pearson sense for Laplace noise, and while the presence of high amplitude samples in the noise have been confirmed, the samples generally occur in bursts lasting a very short time. The arctic data also has Gaussian characteristics much of the time. Combining the above, we would expect that (D1) would be better than (D2). Our results agree with this hypothesis. Due to the nonstationary nature of the noise, the time-varying detectors were both expected to outperform the linear detector. As predicted, the performance levels of (D3) and (D4) were superior to (D1). The figure also indicates that there is essentially no difference in performance levels for (D3) and (D4).

A more informative comparison between these two detectors is displayed in Figure 2. This is a plot of the ratio of power levels achieved for $\alpha = 0.10$ on a block-by-block basis. Note that the mean of β_3/β_4 is almost unity and the variance is very small. For the generalized Gaussian density written in the above form with zero mean, the Neyman-Pearson optimal nonlinearity t(x) has the form:

$$t(x) = -b^c |x-s|^c + b^c |x|^c$$

As c varies around the value of 2, t(x) becomes nonlinear, but the change is small and slow, so that if c is near 2, then t(x) is nearly linear. In fact, for this data, the average value of c that (D4) was adjusted to was 2.16, with $c \in [1.75, 2.25]$ for most blocks. This implies, that based on the sample kurtosis, the detector thought the arctic data to be slightly lighter

tailed than Gaussian. Given this information, the similar performance levels of (D3) and (D4) are understandable.

In order to gain an understanding of the frequency content of the arctic data, power spectra were computed for 0.5 second blocks of data, from the beginning to the end of the data set. In agreement with [7,8], high powered tonals which change center frequency and amplitude are apparent throughout the data set, where the tones are normally in the frequency band 0.8 - 1.8 kHz, with resonances often at higher frequencies. In an effort to understand how these tonals affect the statistics of the arctic noise both epdf's and power spectra were computed, for blocks of 5 records. Unexpectedly, there appears to be an association between the overall shape of the power spectrum and the shape of the epdf.

Specifically, for blocks whose power spectra show high-powered tonals, the epdf differs markedly from Gaussian - principally in becoming light-tailed. Recall that adding a sinusoid (of random phase and amplitude) to Gaussian noise will result in lighter tails than Gaussian, and that [8] proposed the arctic noise could be modeled as a mixture which includes a Gaussian background plus added sinusoids of random amplitude and phase. Figure 3 is an example of this phenomenon. The periodogram, 3(a), shows a high powered tonal centered at 1125 Hz with what appears to be a resonance at 2250 Hz. In 3(b), the epdf for the same data, and a Gaussian curve are plotted, with the tails enlarged in 3(c). The epdf for this block has heavier shoulders, flatter center, and lighter tails than Gaussian. For this particular block, (D4) had a slightly better performance level than (D3).

For blocks whose power spectra show moderate amplitude resonances, typically the epdf is more peaked and heavier-tailed than Gaussian. An example is shown in Figure 4. Note in particular, that the data has heavier tails than Gaussian, as illustrated in 4(c). For the records used in Figure 4, we find (D3) is marginally better than (D4). This could be due to the limited ability of our detector to model records which have a large kurtosis. Finally, for blocks whose power spectra appear to have no distinguishing characteristics (no visible resonances or spikes), the epdf resembles a Gaussian curve.

Now that we had some understanding of the association between the power spectrum and epdf for a data block, we decided to use this knowledge in the hope of gaining a better understanding of the statistics of the arctic under-ice noise. The obvious place to begin is with the blocks which have high powered tonals in their power spectra. We decided to preprocess the data, with the goal that the processed data would be Gaussian in nature.

A common technique used in signal processing to separate a sinusoidal signal of unknown frequency from background noise is to use an adaptive notch filter (ANF). The ANF is either recursive or non-recursive, and based on the data adjusts parameters to move the center frequency of the notch. Generally, there is also a parameter to adjust the width of the notch, which may be adaptive or fixed. This technique was used on blocks which had a high powered tonal in their power spectrum. The particular filter used was [1]:

$$H(z) = \frac{1 + bz^{-1} + z^{-2}}{1 + \gamma bz^{-1} + \gamma^2 z^{-2}}$$

where b determines the center frequency of the notch and γ determines the width of the notch. Generally, $\gamma \in [0.8,0.95]$ for best results. The actual value of b is found by a simple gradient search algorithm and is the only adaptive parameter for the filter. The idea was

to remove as much of the power of the tones as possible and then determine if the resulting background noise was Gaussian. In contrast to the ideal nonlinearity suggested by [10], we used time domain processing.

As an example, records 4101-4105 were processed in this fashion. The notch width γ was fixed at the value of 0.85. Increasing γ resulted in removing too little of the power of the narrowband component, while decreasing γ resulted in removing too much power not associated with the narrowband component. The spectrum of the filtered data is shown in Figure 5. Note that the narrowband component centered at 1125 Hz has a significantly lower power, though it was not removed completely, and that the resonance appears not to be affected by the filtering. To determine what effect the reduction of the tonal power had on the shape of the epdf, the filtered data was then used to compute a new epdf. Plotted in Figure 6, are the original and filtered epdf's, along with a Gaussian curve of mean zero and variance unity. The filtered data has lighter shoulders and heavier tails than the unfiltered data, and the epdf compares well with the Gaussian curve. Processing other blocks which had a high powered tonal yielded similar results.

A comparison was made between the performance levels of the filtered and raw data for these same records. The time varying linear detector (D3) was used for this purpose. Figure 7 is a plot of Figure 1 but including the (α,β) curves for the raw and filtered data. First note that due to the asymmetry of the epdf's, the power curve is not completely symmetric. Also recall that the performance levels for (D3) and (D4) are average power levels for each α . We see that filtering the data does result in an increase in the power level. Note also that the power level for the filtered data compares well with the average power achieved by (D3).

SUMMARY

While the generalized Gaussian model seems to fit the empirical probability density function plots of the arctic data fairly well, there is no detection advantage apparent. This suggests that, for purposes of detection, there is no reason to increase the complexity to use this model. It is also clear, that at the very least a time-varying detector structure should be used, and most likely an adaptive structure would yield the best results.

It was shown that, for blocks which contain a high powered tonal, an adaptive notch filter can be used to preprocess the data, which results in more nearly Gaussian data and a performance improvement. There are several problems with using such a structure however. If one uses a sinusoidal carrier, then precautions must be taken to insure the filter does not remove the signal. Care must also be taken to insure that the filter can handle multiple narrowband components, and that it becomes all-pass when there exists no narrowband component. The adaptive notch filter does not address the problem suggested in Figure 4. That is, the ANF is not a proper preprocessing method for data which is heavy tailed relative to Gaussian.

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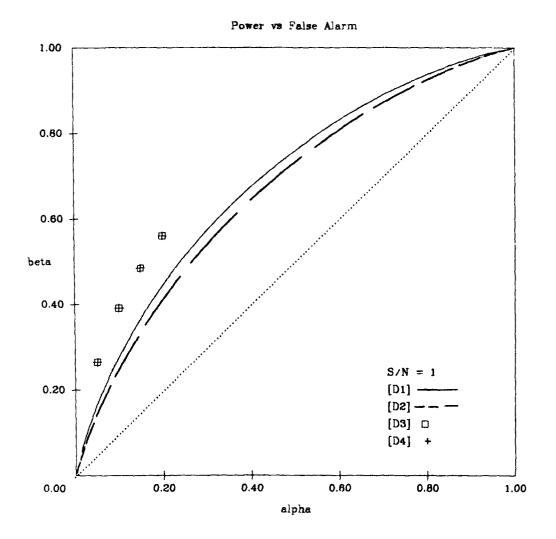


Figure 1

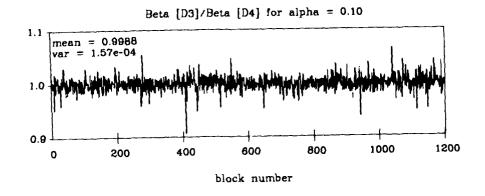
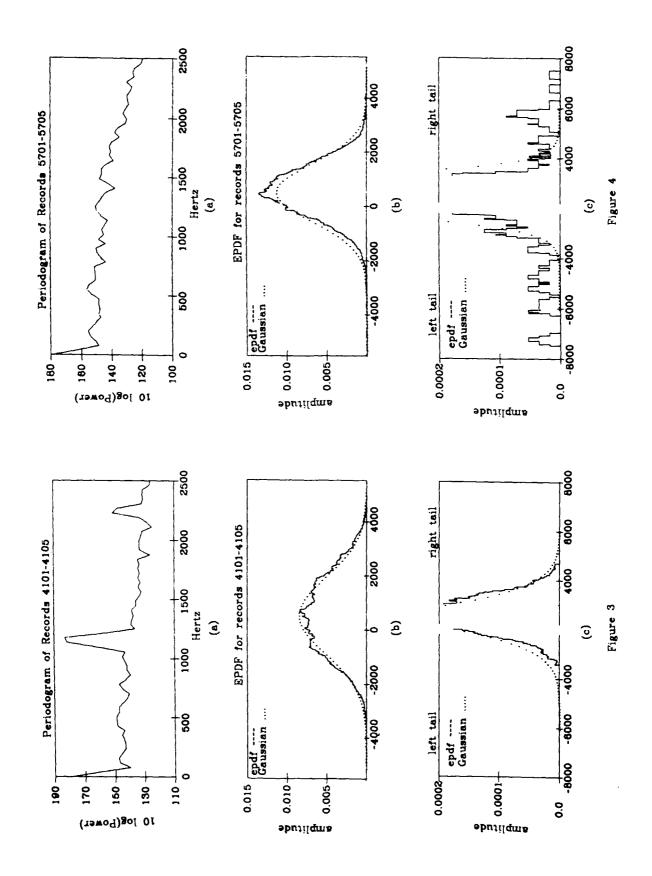
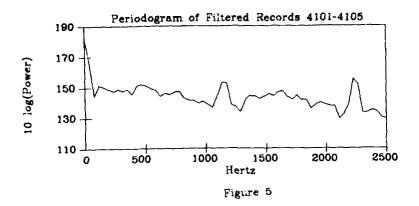
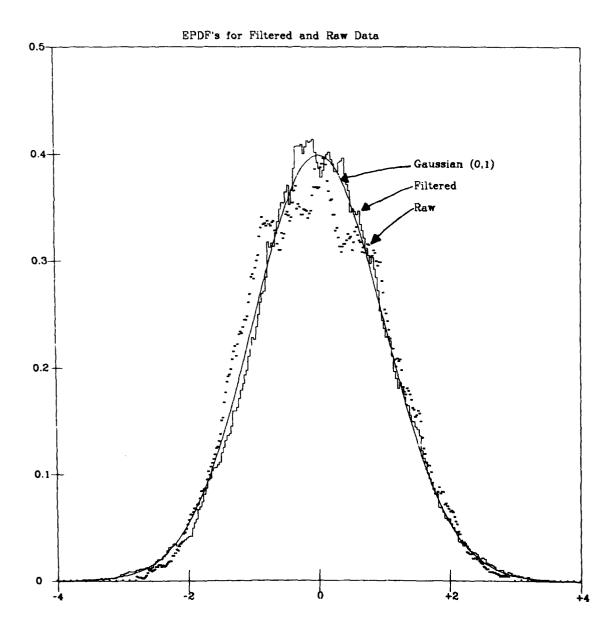
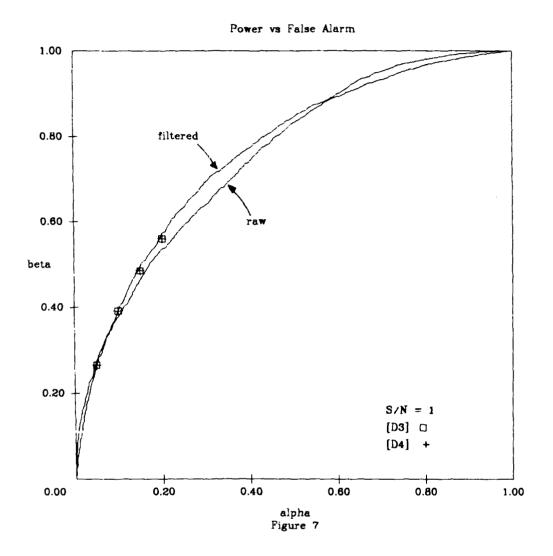


Figure 2









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